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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No.	Applicant(s)
	10/802,151	KIM ET AL.
	Examiner	Art Unit
	Ian Jen	3609

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☐ Responsive to communication(s) filed on _____.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-40* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-40* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *16 March 2004* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

KHOI H. TRAN
SUPERVISORY PATENT EXAMINER
Khoi H. Tran

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date *3/16/2004*.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____.

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

DETAILED ACTION

Claim Rejections - 35 USC § 102

1. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

> A person shall be entitled to a patent unless –(b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.

2. **Claims 1 -3, 21,22,24,25 are rejected under 35 U.S.C. 102(b) as being anticipated by Pettigrew (US Pat No. 5,018,096).**

As for claim 1, Pettigrew shows a method of analyzing a turbine engine to determine a normal engine condition or a faulty engine condition (Abstract, Fig 4), said method comprising the steps of: acquiring at least one engine operating parameter (Column 3, lines 21 -24; Column 3 , lines 37 -42); calculating at least one engine residual value from said at least one engine operating parameter(Column 3, lines 46-49); normalizing said at least one engine residual value to yield at least one normalized engine residual (Column 10, lines 43 - 54); mapping, via a clustering technique, said at least one normalized engine residual as at least one input vector into an engine condition space having a plurality of clusters, each of said plurality of clusters representing either a normal vector engine condition or a faulty vector engine condition; (Column 5, lines 5 - 21; Column 5, lines 35 - Column 63; Column 11, lines 48 - 51; Table 1 where REDD value is the normalized engine residual and HI/LO/OK represents different clusters with respect to different engine parameter as the engine condition space; Fig 5, step 238, 242,240) identifying a closest cluster within said engine condition space, said closest cluster being closer to said at least one input vector than any other of said plurality of clusters (Table 2

where input data are being closer as in normal condition and further specified into different cluster groups; Table 3 where the input data are being closer to abnormal condition and further specified into different cluster groups; Column 11, lines 8-32); and determining a normal engine condition for the engine undergoing analysis if said closest cluster represents a normal vector engine condition(Column 10, lines 54 - 65; Table 2 where input data are shown as in normal condition; Table 3 where the input data are shown in abnormal condition; Fig 5), and determining a faulty engine condition for the engine undergoing analysis if said closest cluster represents a faulty vector engine condition (Column 11, lines 8 - 32; Fig 5, Step 242).

As for claim 2, Pettigrew shows the engine operating parameter is selected from the group consisting of: core speed, exhausted gas temperature, and fuel flow (Column 3, lines 36 - 42).

As for claim 3 , Pettigrew shows the step of acquiring at least one engine operating parameter comprises the step of collecting engine operating data in the field(Fig 4, Step 200,202, 204; Column 4, lines 16 -21).

As for claim 21, Pettigrew shows the faulty engine condition is selected from the group consisting of: an exhaust temperature sensor failure, a combustor liner burn-through failure, and a bleed band leakage failure (Table 1; Column 6, lines 64 - Column 7, lines 12 where failures are addressed in the table).

As for claim 22, Pettigrew shows a computer readable medium having computer-executable instructions for performing a method,(Fig 2, processor 112; Column 4,

lines 16-54) wherein said method comprises: calculating at least one engine residual parameter from data generated from a engine model and from engine operating data collected in the field from an engine undergoing analysis parameter (Column 3, lines 21 -24; Column 3 , lines 37 -42; Column 3, lines 46-49); normalizing said at least one engine residual value to yield at least one normalized engine residual (Column 10, lines 43 - 54); mapping via a clustering technique said at least one normalized engine residual as at least one input vector into an engine condition space having plurality of clusters, each of said plurality of clusters representing either a normal vector engine condition or a faulty vector engine condition (Column 5, lines 5 - 21; Column 5, lines 35 - Column 63; Column 11, lines 48 - 51; Table 1 where REDD value is the normalized engine residual and HI/LO/OK represents different clusters with respect to different engine parameter as the engine condition space; Fig 5, step 238, 242,240); identifying a closest cluster within said engine condition space, said closest cluster being closer to said at least one input vector than any other of said plurality of clusters (Table 2 where input data are being closer to normal condition and further specified into different cluster groups; Table 3 where the input data are being closer abnormal condition and further specified into different cluster groups; Column 11, lines 8-32); and determining a normal engine condition for the engine undergoing analysis if said closest cluster represents a normal vector engine condition, and determining a faulty engine condition for the engine undergoing analysis if said closest cluster represents a faulty vector engine condition (Column 11, lines 8 - 32; Fig 5, Step 242).

As for claim 24, Pettigrew shows the method further comprises inputting into the computer engine operating data collected in the field (Fig 4, Step 200,202, 204; Column 4, lines 16 -21 where the data is stored in the computer readable medium).

As for claim 25, Pettigrew shows the method further comprises inputting into the computer standard engine characteristics obtained from said engine model (Fig 5 where the REDD data, which is engine residual value, is compared against in step 238, 242, 240, with empirical engine model data; Column 10, lines 10-42).

Claim Rejections - 35 USC § 103

3. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

4. **Claim 4- 8, 15, 16, 23, 26-29, are rejected under 35 U.S.C. 103(a) as being unpatentable over Pettigrew (US Pat No. 5,018,096) in view of Nomura et al (US Pat No. 5,311,421).**

As for claim 4, Pettigrew shows the step of calculating said at least one engine residual value comprises the step of comparing said at least one engine operating parameter with standard engine characteristics (Fig 5 where the REDD data, which is engine residual value, is compared against in step 238, 242, 240, with empirical engine model data; Column 10, lines 10-42). Pettigrew does not show the data is from an empirical engine model. Nomura et al further shows; the engine operating parameter is obtained from empirical engine model (Fig 2, where multi layer neural network can be treated as empirical data model; Column 13, lines 25 - 30).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model by adding mathematical transfer function, as taught by Nomura et al, since the polynomial

function of engine fan speed in multi layer neural network is a common mathematical representation that can be used on various systems. The modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art because the modification of Pettigrew in view of Nomura et al yields predictable result of providing mathematical representation of a turbine system.

As for claim 5 , Pettigrew shows a method to analyze turbine engine model by using statistical method but does not shows a method of claim 4 wherein said empirical engine model comprises a polynomial function of engine fan speed, which represent the transfer function of turbine engine system input and output. Nomura et al further shows a generic polynomial function in empirical model as a mathematical transfer function in representation of a system (Column 13, lines 25 - 30).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model by providing mathematical transfer function, as taught by Nomura et al, since the polynomial function of engine fan speed is a common mathematical model that can be used to describe ~~on~~ various systems. The modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art because the modification of Pettigrew in view of Nomura et al yields predictable result of providing mathematical representation of a turbine system.

As for claim 6, Pettigrew does not show a neural network. Nomura et al shows that neural network is provided for teaching dynamic systems. Teaching using neural network is commonly well known in the art. (Fig 2; Fig 3; Fig 18, Neural Network 45; Column 4, lines 38-Column 5, lines 6).

It would have been obvious for one of ordinary skill in the art to provide a commonly well known neural network to Pettigrew, 069, as taught by Nomura et al because it provides an automated teaching model for a complex dynamic system.

As for claim 7 , Pettigrew et al shows the step of calculating said at least one engine residual value comprises the step of comparing said at least one engine operating parameter with standard engine characteristics (Fig 5, Step 238,242,240; Column 11, lines 24 - 31, TEAC data 240; Test cell data 238; Inflight data 242). Pettigrew does not show the operating parameter with standard engine characteristic obtained from a first principle engine model. Nomura et al further shows the operating parameter with standard engine characteristic obtained from a first principle engine model. (Column 3, lines 6 - 26)

It would have been obvious for one of ordinary skill in the art to provide the system of Pettigrew by first principle engine model of Nomura et al since the first principle engine model are a differential equation modeling for describing a dynamic system with respect to each characteristic and variable to be test and sensed under computer simulation environment.

As for claim 8, Pettigrew shows a method to analyze turbine engine model by using statistical method but does not shows the first principle engine model comprises a differential equation representing dynamics of the turbine engine. Nomura et al further shows a differential equation representing dynamics of the turbine engine (Column 3, lines 5 - 27).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model by differential equation, as taught by Nomura et al, since differential equations are mathematical representations that can be used to describe ~~on~~ various systems. The modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art

because the modification of Pettigrew in view of Nomura et al yields predictable result of providing mathematical representation of a turbine system.

As for claim 15, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the clustering technique mapping comprises a self-organizing map. Nomura et al further shows the clustering technique mapping comprises a self-organizing map (Fig 2, Fig 3, where multi layer network is built based on single layer network, which is the form of self -organizing map, a sub type of neural network; Column 10, lines 1 - 60).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model by single layer network, self-organizing map, as taught by Nomura et al, since the self-organizing map is a commonly well know class of neural network. The modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art because the modification of Pettigrew in view of Nomura et al yields predictable results of providing commonly well known class of neural network for teaching purposes.

As for claim 16, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of training said self-organizing map for a plurality of epochs using data from a plurality of turbine engines. Nomura et al further shows the step of training said self-organizing map for a plurality of epochs using data from a plurality of turbine engines(Fig 2, Fig 3, where multi layer network, which processes input signal at different time periods at various layer is built based on single layer networks, which is the form of self -organizing map, a sub type of neural network; Column 10, lines 1 - 60; Column 21, lines 45 - Column 22, lines 61).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model by multi layer network, as taught by Nomura et al, since the multi layer network, which is

the combination of single layer network that accepts and processes input signal at various time periods, is a mathematical representation that can be used to describe on various systems. The modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art because the modification of Pettigrew in view of Nomura et al yields predictable results of providing mathematical representation of a turbine system.

5. Claim 9-14, 17-20, 23,26-29,31-34 are rejected under 35 U.S.C. 103(a) as being unpatentable over Pettigrew (US Pat No. 5,018,096) in view of Goebel et al (US Pat No. 6,408,259).

As for claim 9, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of normalizing comprises the step of normalizing a mean of said at least one engine residual value to zero. Goebel et al further shows the step of normalizing comprises the step of normalizing a mean of said at least one engine residual value to zero (Fig 3, where the data error, which is residual value, is minimized; Column 7, lines 28 - Column 8, lines 15 where the normalization technique is discussed using Normalize 32).

It would have been obvious for one of ordinary skill in the art to provide the turbine diagnostic system of Pettigrew by adapting the normalize technique of Goebel et al in order to continuously monitor and simultaneously provide the turbine system input and output to achieve real time data correction since the normalization factor technique on the standard deviation and mean is a common mathematical form of expression and can be applied on various systems.

As for claim 10, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of normalizing comprises the step of normalizing a standard

derivation of said at least one engine residual value to unity. Goebel et al further shows the step of normalizing comprises the step of normalizing a standard derivation of said at least one engine residual value to unity (Fig 3, where the data error, which is residual value, is minimized and therefore create standard deviation equal to one since the variance is not existed; Column 7, lines 28 - Column 8, lines 15 where the normalization technique is discussed using Normalize 32).

It would have been obvious for one of ordinary skill in the art to provide the turbine diagnostic system of Pettigrew by adapting the normalize technique of Goebel et al in order to continuously monitor and simultaneously provide the turbine system input and output to achieve real time data correction since the normalization factor technique on the standard deviation and mean is a mathematical form expression and can be applied on various systems.

As for claim 11, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of normalizing comprises the step of obtaining a normalization factor from a parameter distribution of a normally-operating baseline engine. Goebel et al further shows the step of normalizing comprises the step of obtaining a normalization factor from a parameter distribution of a normally-operating baseline engine (Fig 2, where the data input is obtained from a flight engine; Column 5 lines 35 - Column 6, lines 75 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 12, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving an updated normalization factor if said closest cluster represents a normal vector engine condition. Goebel et al further shows the step of deriving an updated normalization factor if said closest cluster represents a normal vector engine condition (Fig 3, where the classifier 33 receive normalized data input and classify data into various cluster where the data classified into normal cluster will be updated and used; Column 7, lines 61 - Column 8, lines 47).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 13, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving an updated normalization factor comprises the steps of multiplying the square of a current mean normalization factor by a first fraction to obtain a first product; obtaining a current engine parameter from the turbine engine; multiplying said current engine parameter by a second fraction to obtain a second product; and adding said first and second products to yield an updated mean normalization factor. Goebel et al further shows the step of deriving an updated normalization factor comprises the steps of multiplying the square of a current mean normalization factor by a first fraction to obtain a first product; obtaining a current engine parameter from the turbine engine; multiplying said current engine parameter by a second fraction to obtain a second product; and adding said first and second

products to yield an updated mean normalization factor(Column 5 lines 35 - Column 7, lines 10; Column 8, lines 15 - 45 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form on various systems).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 14, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving an updated normalization factor comprises the steps of multiplying the square of a current standard deviation normalization factor by a first fraction to obtain a first product; subtracting an updated mean normalization factor from said current engine parameter to obtain a first difference; multiplying the square of said first difference by a second fraction to obtain a second product; subtracting a current mean normalization factor from said current engine parameter to obtain a second difference; multiplying the square of said second difference by a third fraction to obtain a third product; and, taking the square root of said first, second, and third products to yield an updated standard deviation normalization factor. Goebel et al further shows the step of deriving an updated normalization factor comprises the steps of multiplying the square of a current standard deviation normalization factor by a first fraction to obtain a first product; subtracting an updated mean normalization factor from said current engine parameter to obtain a first difference; multiplying the square of said first difference by a second fraction to obtain a second product; subtracting a current mean normalization factor from said current engine parameter to obtain a second

difference; multiplying the square of said second difference by a third fraction to obtain a third product; and, taking the square root of said first, second, and third products to yield an updated standard deviation normalization factor.(Column 5 lines 35 - Column 7, lines 10; Column 8, lines 15-45 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form on various systems).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 17, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the clustering technique mapping comprises a method from the group consisting of fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method. Goebel et al further shows the clustering technique mapping comprises a method from the group consisting of fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method (Column 8, lines 5 - Column 9, lines 25, where fuzzy KNN algorithm is fuzzy clustering utilizing k-means algorithm, which is an algorithm to cluster data based on attributes into k partitions; where persistency checker 38 determines the vigilance level, which is the matching criterion for adaptive resonance theory; where gaussian mixture method is a mean to partition data sample, into various clusters utilizing data density on the data sample; Column 6, lines 39-66 where the center point is the density center point).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and

mapping since statistical mathematical algorithm and method to mining data by utilizing fuzzy clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 18, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving a belief factor, said belief factor being a function of said normal vector engine condition or said faulty vector engine condition. Goebel et al further shows the step of deriving a belief factor, said belief factor being a function of said normal vector engine condition or said faulty vector engine condition (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each variable).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 19, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the faulty engine condition is determined for the turbine engine, said belief factor comprises a value derived by subtracting from unity a ratio obtained by dividing a closest distance between said at least one input vector and said closest cluster by a next-closest distance between said at least one input vector and a next closest cluster. Goebel et al further shows the faulty engine condition is determined for the turbine engine, said belief factor

comprises a value derived by subtracting from unity a ratio obtained by dividing a closest distance between said at least one input vector and said closest cluster by a next-closest distance between said at least one input vector and a next closest cluster(Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each input variable along with nearby cluster).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval by subtracting unity, which is one, to variance is well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 20, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the normal engine condition is determined for the turbine engine, said belief factor comprises a value derived by subtracting from unity a maximum ratio of the set of ratios obtained by dividing a distance between said at least one input vector and said closest cluster by each of a set of respective fault distances between said at least one input vector and all clusters representing a faulty vector engine condition. Goebel et al further shows the normal engine condition is determined for the turbine engine, said belief factor comprises a value derived by subtracting from unity a maximum ratio of the set of ratios obtained by dividing a distance between said at least one input vector and said closest cluster by each of a set of respective fault distances between said at least one input vector and all clusters representing a faulty vector engine condition(Column 9, lines 14- 25; Column 5, lines 4-20 where the belief

factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each input variable along with nearby cluster).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval by subtracting unity, which is one, to maximum variance is well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 23, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the clustering technique mapping comprises a method from the group consisting of self-organizing mapping, fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method. Goebel et al further shows the clustering technique mapping comprises a method from the group consisting of self-organizing mapping, fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method (Column 8, lines 5 - Column 9, lines 25, where fuzzy KNN algorithm is fuzzy clustering utilizing k-means algorithm, which is an algorithm to cluster data based on attributes into k partitions; where persistency checker 38 determines the vigilance level, which is the matching criterion for adaptive resonance theory; where gaussian mixture method is a mean to partition data sample, into various clusters utilizing data density on the data sample; Column 6, lines 39-66 where the center point is the density center point).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and mapping since statistical mathematical algorithm and method to mining data by utilizing fuzzy

clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 26, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method further comprises inputting into the computer normalization factors obtained from a normally-operating baseline engine. Goebel et al further shows the method further comprises inputting into the computer normalization factors obtained from a normally-operating baseline engine (Fig 2, where the data input is obtained from a flight engine; Column 5 lines 35 - Column 6, lines 75 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 27, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method further comprises calculating a closest distance between said at least one input vector and said closest cluster. Goebel et al further shows the method further comprises calculating a closest distance between said at least one input vector and said closest cluster (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each input variable along with nearby cluster).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval by subtracting unity, which is one, to variance is well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 28, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method further comprises calculating a belief factor, in response to a determination of said faulty engine condition, by dividing said closest distance by a next-closest distance between said at least one input vectors and a next closest cluster and subtracting the result from unity. Goebel et al further shows the method further comprises calculating a belief factor, in response to a determination of said faulty engine condition, by dividing said closest distance by a next-closest distance between said at least one input vectors and a next closest cluster and subtracting the result from unity (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each variable).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 29, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method further comprises calculating a belief factor, in response to a determination that the engine condition is normal, by subtracting from unity a maximum ratio from the set of ratios obtained by dividing said closest distance by each of a set of respective fault distances between said input vectors and the set of all clusters representing a faulty condition. Goebel et al further shows the method further comprises calculating a belief factor, in response to a determination that the engine condition is normal, by subtracting from unity a maximum ratio from the set of ratios obtained by dividing said closest distance by each of a set of respective fault distances between said input vectors and the set of all clusters representing a faulty condition (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each variable).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval statistical mathematical algorithm and method to calculating data to form a belief factor or confidence interval is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 31, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show a method of analyzing a turbine engine to determine a normal engine condition or a faulty engine condition, said method comprising the steps of: acquiring a plurality of engine operating parameters from the turbine engine under analysis. Goebel et al further shows a method of analyzing a turbine engine to determine a normal engine condition or a faulty engine condition, said method comprising the steps of: acquiring a plurality of engine operating

parameters from the turbine engine under analysis(Fig 3, where inflight data is directly obtained from turbine engine toward database; Column 3, lines 21 -24; Column 3 , lines 37 -42); calculating a corresponding plurality of engine residual values by comparing each of said engine operating parameters with standard engine characteristics obtained from an engine model (Fig 4, where divEGT is the residual value and dEGT contains standard engine characteristic obtained from engine model ; Column 5, lines 39 - 65); computing the mean and the standard deviation of each of said plurality of engine residual values(Column 5, lines 35 - Column 6, lines 38); normalizing each of said plurality of engine residual values by normalizing said mean to zero and by normalizing said standard deviation to unity to yield a plurality of normalized engine residuals, said step of normalizing using normalization factors obtained from a parameter distribution of a normally-operating baseline engine (Fig 3, where the data error, which is residual value, is minimized; Column 7, lines 28 - Column 8, lines 15 where the normalization technique is discussed using Normalizer 32; Fig 3, where the data error, which is residual value, is minimized and therefore create standard deviation equal to one since the variance is not existed; Column 7, lines 28 - Column 8, lines 15 where the normalization technique is discussed using Normalizer 32); mapping, via a clustering technique, said normalized engine residuals as input vectors into an engine condition space having a plurality of clusters, each said cluster representing either a normal vector engine condition or a faulty engine vector condition (Column 4, lines 42 -66 where data is classified); identifying a closest cluster within said engine condition space, said closest cluster being closer to said input vectors than any other of said plurality of clusters (Column 7, lines 61 - Column 8, lines 47); and determining a normal engine condition for the engine under analysis if said closest cluster represents a normal vector engine condition, and determining a faulty engine condition for the engine under analysis if said closest cluster represents a faulty vector engine condition(Column 7, lines 61 - Column 8, lines 47).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and mapping since statistical mathematical algorithm and method to obtain mean and standard deviation and to mining data by utilizing fuzzy clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 32, Pettigrew shows plurality of engine operating parameters comprises a core speed measurement, an exhausted gas temperature measurement, and a fuel flow measurement (Column 3, lines 36 - 42).

As for claim 33, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the clustering technique mapping comprises a method from the group consisting of self-organizing mapping, fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method. Goebel et al further shows the clustering technique mapping comprises a method from the group consisting of self-organizing mapping, fuzzy clustering, adaptive resonance theory, K-means algorithm, and Gaussian mixture method (Column 8, lines 5 - Column 9, lines 25, where fuzzy KNN algorithm is fuzzy clustering utilizing k-means algorithm, which is an algorithm to cluster data based on attributes into k partitions; where persistency checker 38 determines the vigilance level, which is the matching criterion for adaptive resonance theory; where gaussian mixture method is a mean to partition data sample, into various clusters utilizing data density on the data sample; Column 6, lines 39-66 where the center point is the density center point).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and mapping since statistical mathematical algorithm and method to mining data by utilizing fuzzy clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 34, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving a belief factor wherein, if turbine engine condition is determined to be faulty, said belief factor comprises a value derived by subtracting from unity a ratio obtained by dividing a distance between said input vectors and said closest cluster by a distance between said input vectors and a next closest cluster, and wherein, if said engine is determined to be normal, said belief factor comprises a value derived by subtracting from unity a maximum ratio of the set of ratios obtained by dividing a distance between said input vectors and said closest cluster by each of the set of fault distances between said input vectors and all clusters representing a faulty condition. Goebel et al further shows the step of deriving a belief factor wherein, if turbine engine condition is determined to be faulty, said belief factor comprises a value derived by subtracting from unity a ratio obtained by dividing a distance between said input vectors and said closest cluster by a distance between said input vectors and a next closest cluster, and wherein, if said engine is determined to be normal, said belief factor comprises a value derived by subtracting from unity a maximum ratio of the set of ratios obtained by dividing a distance between said input vectors and said closest cluster by each of the set of fault distances between said input vectors and all clusters representing a faulty condition. (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is

determined by the composite alert score generator 40 in alert evaluator 29 with respect to each input variable along with nearby cluster).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method used to calculating data to form a belief factor or confidence interval by subtracting unity, which is one, to variance is well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

6. **Claim 30, 35 -40 are rejected under 35 U.S.C. 103(a) as being unpatentable over Pettigrew (US Pat No. 5,018,096) in view of Nomura et al (US Pat No. 5,311,421) as applied to claims 5- 8,15,16,30 above, and further in view of Goebel et al (US Pat No. 6,408,259).**

As for claim 30, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method further comprises inputting data from a plurality of turbine engines into said self-organizing map to train said self-organizing map. Nomura et al further shows method further comprises inputting data from a plurality of turbine engines into said self-organizing map to train said self-organizing map (Fig 2, Fig 3, where multi layer network is built based on single layer network, which is the form of self -organizing map, a sub type of neural network possess short term memory to be trained or affected by the future input signal; Column 10, lines 1 - 60).

It would have been obvious for one of ordinary skill in the art to provide turbine engine model of Pettigrew by single layer network, self-organizing map, of Nomura et al since the self-organizing map is a mathematical representation that can be used on various systems. The

modification of Pettigrew in view of Nomura et al would have been obvious to one of ordinary skill in the art because the modification of Pettigrew in view of Nomura et al yields predictable result of providing mathematical representation of a turbine system. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 35, Pettigrew shows a method of analyzing a turbine engine to determine a normal engine condition or a faulty engine condition, said method comprising the steps of: acquiring a core speed reading, an exhaust gas temperature reading, and a fuel flow reading for the turbine engine under analysis flow (Column 3, lines 36 - 42); calculating a core speed residual value, an exhaust gas temperature residual value, and a fuel flow residual value by comparing said core speed reading, said exhaust gas temperature reading, and said fuel flow reading (Fig 5 where the REDD data, which is engine residual value, is compared against in step 238, 242, 240, with empirical engine model data; Column 10, lines 10-42); mapping said normalized core speed residual, said normalized exhaust gas temperature residual, and said normalized fuel flow residual as respective input vectors into an engine condition space having a plurality of clusters, each said cluster representing either a normal vector engine condition or a faulty vector engine condition (Column 5, lines 5 - 21; Column 5, lines 35 - Column 63; Column 11, lines 48 - 51; Table 1 where REDD value is the normalized engine residual and HI/LO/OK represents different clusters with respect to different engine parameter as the engine condition space; Fig 5, step 238, 242,240)

Pettigrew does not show inputting data into a self-organizing map from a plurality of reference turbine engines to train said self-organizing map; the comparison data from standard

engine characteristics obtained from an engine model; computing the mean and the standard deviation of each of said core speed residual value, said exhaust gas temperature residual value, and said fuel flow residual value; normalizing each of said core speed residual value, said exhaust gas temperature residual value, and said fuel flow residual value by normalizing said respective means to zero and by normalizing said standard deviation to unity to yield a normalized core speed residual, a normalized exhaust gas temperature residual, and a normalized fuel flow residual, said step of normalizing using normalization factors obtained from a parameter distribution of a normally-operating baseline engine; and identifying a closest cluster within said engine condition space, said closest cluster being closer to said input vectors than any other of said plurality of clusters; and, determining a normal engine condition for the engine under analysis if said closest cluster represents a normal vector engine condition, and determining a faulty engine condition for the engine under analysis if said closest cluster represents a faulty vector engine condition.

Nomura et al further shows, inputting data into a self-organizing map from a plurality of reference turbine engines to train said self-organizing map (Fig 2, Fig 3, where multi layer network is built based on single layer network, which is the form of self -organizing map, a sub type of neural network possess short term memory to be trained or affected by the future input signal; Column 10, lines 1 - 60); the comparison data obtained from standard engine characteristics obtained from an engine model (Fig 2, where multi layer neural network can be treated as empirical data model; Column 13, lines 25 - 30).

Goebel et al further shows, computing the mean and the standard deviation of each of said core speed residual value, said exhaust gas temperature residual value, and said fuel flow

residual value; normalizing each of said core speed residual value, said exhaust gas temperature residual value, and said fuel flow residual value by normalizing said respective means to zero and by normalizing said standard deviation to unity to yield a normalized core speed residual, a normalized exhaust gas temperature residual, and a normalized fuel flow residual, said step of normalizing using normalization factors obtained from a parameter distribution of a normally-operating baseline engine (Column 5 lines 35 - Column 7, lines 10; Column 8, lines 15 - 45 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form on various systems and residual values); and identifying a closest cluster within said engine condition space, said closest cluster being closer to said input vectors than any other of said plurality of clusters (Column 7, lines 61 - Column 8, lines 47); and, determining a normal engine condition for the engine under analysis if said closest cluster represents a normal vector engine condition, and determining a faulty engine condition for the engine under analysis if said closest cluster represents a faulty vector engine condition (Column 7, lines 61 - Column 8, lines 47).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and mapping since statistical mathematical algorithm and method to obtain mean and standard deviation and to mining data by utilizing fuzzy clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 36, Pettigrew shows the step of calculating a closest distance between said at least input vectors and said closest cluster (Table 2 where input data are being closer to normal

condition and further specified into different cluster groups; Table 3 where the input data are being closer abnormal condition and further specified into different cluster groups; Column 11, lines 8-32).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive the predictable results of data clustering and mapping since statistical mathematical algorithm and method used to obtain mean and standard deviation and to mining data by utilizing fuzzy clustering, adaptive resonance theory, k-means algorithm and Gaussian mixture method is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 37, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of calculating a belief factor for said faulty engine condition by dividing said closest distance by a next-closest distance between said input vectors and a next closest cluster and subtracting the result from unity. Goebel et al further shows the step of calculating a belief factor for said faulty engine condition by dividing said closest distance by a next-closest distance between said input vectors and a next closest cluster and subtracting the result from unity. (Column 9, lines 14- 25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each variable).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method used to calculating data to form a belief factor or

confidence interval is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 38, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the method of the step of calculating a belief factor for said normal engine condition by subtracting from unity a maximum ratio from the set of ratios obtained by dividing said closest distance by a fault distance between said input vectors and the set of all clusters representing a faulty condition. Goebel et al further shows the method of the step of calculating a belief factor for said normal engine condition by subtracting from unity a maximum ratio from the set of ratios obtained by dividing said closest distance by a fault distance between said input vectors and the set of all clusters representing a faulty condition(Column 9, lines 14-25; Column 5, lines 4-20 where the belief factor, which is vigilance level, is determined by the composite alert score generator 40 in alert evaluator 29 with respect to each variable).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical algorithm and method to derive a belief factor or confidence interval since statistical mathematical algorithm and method used to calculate calculating data to form a belief factor or confidence interval is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular algorithm and method yield unexpected results in the application.

As for claim 39, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving an updated normalization factor if said closest cluster represents a normal vector engine condition, said step of deriving an updated normalization factor including the steps of multiplying the square of a mean normalization factor

by a first fraction to obtain a first product, obtaining a current engine parameter from the turbine engine, multiplying said current engine parameter by a second fraction to obtain a second product, and adding said first and second products to yield an updated mean normalization factor. Goebel et al further shows the step of deriving an updated normalization factor if said closest cluster represents a normal vector engine condition, said step of deriving an updated normalization factor including the steps of multiplying the square of a mean normalization factor by a first fraction to obtain a first product, obtaining a current engine parameter from the turbine engine, multiplying said current engine parameter by a second fraction to obtain a second product, and adding said first and second products to yield an updated mean normalization factor (Column 5 lines 35 - Column 7, lines 10; Column 8, lines 15 - 45 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form on various systems).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

As for claim 40, Pettigrew disclose all method steps as indicated in the paragraph 2. However, it does not show the step of deriving an updated normalization factor further comprises the steps of multiplying the square of a current standard deviation normalization factor by a third fraction to obtain a third product; subtracting said updated mean normalization factor from said current engine parameter to obtain a first difference; multiplying the square of said first difference by a fourth fraction to obtain a fourth product; subtracting said mean normalization

factor from said current engine parameter to obtain a second difference; multiplying the square of said second difference by said second fraction to obtain a fifth product; and, taking the square root of the sum of said third, fourth, and fifth products to yield an updated standard deviation normalization factor. Goebel et al further shows the step of deriving an updated normalization factor further comprises the steps of multiplying the square of a current standard deviation normalization factor by a third fraction to obtain a third product; subtracting said updated mean normalization factor from said current engine parameter to obtain a first difference; multiplying the square of said first difference by a fourth fraction to obtain a fourth product; subtracting said mean normalization factor from said current engine parameter to obtain a second difference; multiplying the square of said second difference by said second fraction to obtain a fifth product; and, taking the square root of the sum of said third, fourth, and fifth products to yield an updated standard deviation normalization factor. (Column 5 lines 35 - Column 7, lines 10; Column 8, lines 15-45 where the normalization factor is discussed to apply on the standard deviation and mean is discussed in mathematical form on various systems).

It would have been obvious for one of ordinary skill in the art by providing the claimed mathematical equation to derive the predictable results of normalizing at least one engine residual value since statistical mathematical equation to normalize mean and standard deviation of test data is commonly well known in the art. Furthermore, it was not demonstrated that the usage of the particular equation yield unexpected results in the application.

Conclusion

The prior art made of record and not relied upon is considered pertinent to applicant's disclosure. Belvins et al (US Pat No. 6,615,090) shows neural network respect to multivariable used in the control system.

Eryurek et al (US Pat No. 6,532,392) shows a diagnostic system utilizing statistical method.

Schleiss et al (US Pat No. 6,557,118) shows a diagnostic system utilizing statistical method.

Uluyol et al (US Pat Pub No. 2004/0176901) shows a diagnostic system using neural network and cluster method.

Parlos et al (US Pat No. 6,590,362) shows a Neural Network system.

Muramatsu (US Pat No. 6,393,355) shows Neural Network system on turbine engine.

Foslien et al (US Pat No. 7,243,048) shows a diagnostic system with statistical analyze method.

Goebel et al (US Pat No. 6,216,066) shows a diagnostic system utilizing statistical method, classified data and fuzzy cluster.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Ian Jen whose telephone number is 571-270-3274. The examiner can normally be reached on Monday - Friday 8:00-5:00 (EST).

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Khoi Tran can be reached on 571-272-6919. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

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